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Sensor Fault Detection and Diagnosis for a T700 Turboshaft Engine

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Introduction

A PROPOSED intelligent control system (ICS) contains a sensor fault detection, isolation, and accommodation scheme.[1] If the differences between the estimated and sensed system outputs exceed some threshold values, fault detection logic will initiate a parameter estimation algorithm which determines the type and magnitude of the failure. This is achieved through the use of fault parameters, variables defined to convert the model from that of the unimpaired system to that of an impaired one. Once the fault is isolated, the control system will accommodate it, if possible.[2] This Note discusses the technique used for detecting, isolating, and identifying the fault.

The test bed for this research is the T700 turboshaft engine. In the simplified model used here there is one input, fuel flow W_f, and four measured variables, gas generator speed N_g, interturbine gas temperature T_{45}, interturbine gas pressure P_{45}, and power turbine torque output Q_{PT}. Should any of the sensors fail, the engine would appear to be malfunctioning and, if the faulty measurement were fed back through the control system, the engine would operate off the design point.

Sensor Fault Detection and Isolation

The sensor fault detection and isolation scheme is developed using a fault model. Initially a simplified linear perturbation model was developed which switches between several point models for full envelope coverage.[3] The simplified model at an operating point is of the standard form

$$\left.\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) \end{aligned}\right\} \tag{1}$$

The variables in these point models are all normalized with their zero values corresponding to the operating point. It is assumed that the (A, B, C) realization of the system is in α-canonical form,[4] which gives the model certain properties desirable for fault detection.

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The sensor fault model is built on top of Eq. (1) in the form

$$\left.\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y_s(k) &= F_s C x(k) + f_{s0} \end{aligned}\right\} \tag{2}$$

where $y_s(k)$ is the set of normalized sensor readings at time k. In the unimpaired case, F_s is the identity matrix and f_{s0} is the zero vector, thus reducing Eq. (2) to Eq. (1). The diagonal matrix F_s accounts for changes in sensor gain whereas a nonzero f_{s0} represents bias errors.

A nonlinear simulation of the T700 turboshaft engine and load[5] was used to represent the engine. The time step used is 0.060 s.

Past controller outputs as well as the sensor readings are fed through the fault detection model described by Eq. (2), and the resulting estimate of the set of sensed variables is compared to those received from the simulation at the current time step. The differences, or residuals, are checked against threshold values which, when exceeded, activate the fault detection scheme.

The fault detection scheme contains models appropriate for each type of failure, i.e., actuator, component, and sensor. Just as the sensor fault parameters are associated with the C matrix as shown in Eq. (2), the actuator fault parameters are associated with the B matrix and the component fault parameters are associated with the A matrix.[1] When the residual exceeds the activation threshold, an on-line parameter estimation scheme is initiated which calculates the fault parameters, F_s and f_{s0} in the sensor case.

It is important to run the parameter estimation scheme using data from the impaired system so that the results are not skewed by prefailure information. Therefore, the parameter estimation module begins collecting data to use only after the activation threshold is exceeded. A recursive least squares technique with a forgetting factor of 0.98 is used to compute the value of the fault parameters. As long as the fault occurs suddenly, it appears as a step change in the residuals. Thus, for the short time it takes to perform the identification, the measurement signals are rich enough to allow for accurate estimation. The models of the actuator, component, and sensor failures are developed in parallel, and the three sets of fault parameters are computed simultaneously in the ICS.

At each time step, the resulting fault parameters are passed to the hypothesis testing module which determines from the identified parameters which fault occurred. It assumes that only one failure occurs at a time. The result is checked by confirming that the selected model using the identified fault parameters produces a smaller sum of the squared errors (residuals) over a finite time than do the other estimated models using their fault parameters. In this case a moving window of five data points was used for summing the squares of the residuals before comparing the models, resulting in a delay of at least 0.3 s (5 samples × 0.060 s/sample) before the fault is isolated and its magnitude estimated. This data length was experimentally determined to produce reliable results in relatively few samples.

Results

Testing was performed at the 96% power level. There was no noise present in the system. For the first case, a sensor bias of 1.8% of nominal was introduced to the nonlinear simulation's N_g sensor's output at about 0.0 s. As soon as the bias was added, the corrupted signal disrupted all of the other output variables. The fault parameters corresponding to the multiplicative sensor gain F_s converged immediately to their correct values of 1.0 as determined through recursive least squares, indicating no sensor gain failure. Figure 1 shows the bias estimates f_{s0}. The bias estimate for the N_g sensor converged to approximately 0.018 whereas the other bias values stayed near zero. The slight error in the P_{45} bias is attributed to modeling error in the linear point model.

For the second case, the original unity gain of the N_g sensor was scaled by a factor of 0.1 at about 0.0 s. Figure 2 shows the multiplicative gain fault parameters as determined by the recursive least squares technique from past data. It takes significantly longer to converge than the previous example did but eventually the parameter corresponding to the N_g sensor's gain converges to about 0.1 whereas the other three hover near 1.0. Figure 3 displays the estimated values of the bias parameters, which, after some initial hunting, converge to approximately 0.0.

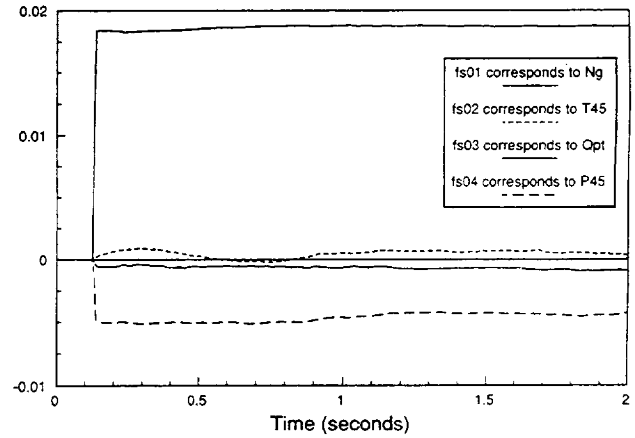

Fig. 1 Bias fault parameters for a 1.8% bias error in N_g sensor.

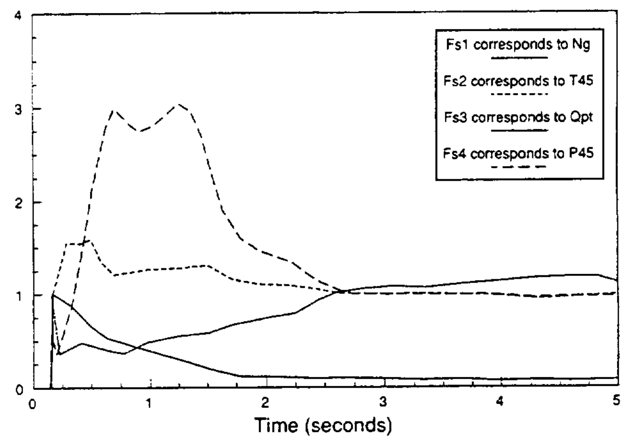

Fig. 2 Multiplicative fault parameters for a 0.1 multiplicative error in N_g sensor.

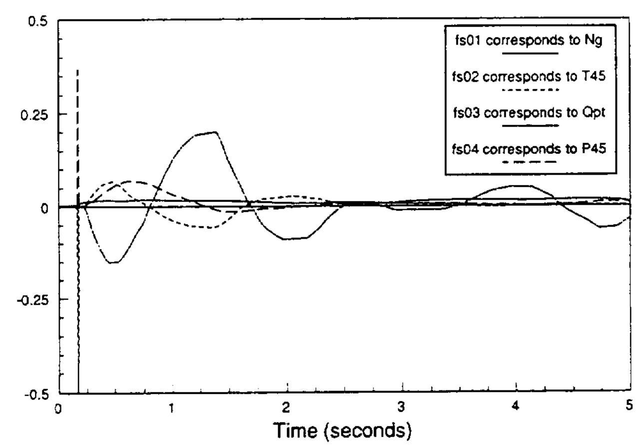

Fig. 3 Bias fault parameters for a 0.1 multiplicative error in N_g sensor.

Conclusions

A scheme to detect, isolate, identify and estimate the type and magnitude of sensor faults in a T700 turboshaft engine has been developed and demonstrated. The injection of a fault caused the residual to exceed the threshold value and trigger the identification scheme. Once running, the scheme produced accurate results reasonably quickly. The identified fault parameters can be used in the state equation by an ICS to eliminate the bias or cancel the incorrect gain, thereby accommodating the sensor faults and allowing the closed-loop system to run as if unimpaired.

Several issues remain to be investigated once noise is included in the system: the effect on threshold values against which residuals are compared, the ability of an appropriate parameter identification technique to provide bias-free estimates, and the minimum number of samples included in the moving window for convergence of the estimates.

Acknowledgment

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